A Learning Methodology for Robotic Manipulation of Deformable Objects

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ABSTRACT

The majority of manipulation systems are designed with the assumption that the objects being handled are rigid and do not deform when grasped. This paper address the problem of robotic grasping and manipulation of 3-D deformable objects, such as rubber balls or bags filled with sand. Specifically, we have developed a generalized learning algorithm for handling of 3-D deformable objects in which prior knowledge of object attributes is not required and thus it can be applied to a large class of object types. A description of our learning methodology will be given in this paper. We outline our methodology for modeling the object deformation and learning the required minimum forces for grasping. Evaluation of the overall algorithm demonstrates that we can achieve an error level of 14% with respect to the minimum physical lifting force.

KEYWORDS: Deformable Objects, Manipulation, Learning

INTRODUCTION

This paper addresses the problem of robotic grasping of 3-D deformable objects. Specifically, we have developed a generalized approach for handling of 3-D deformable objects in which prior knowledge of object attributes is not required and thus can be applied to a large class of object types (e.g. asymmetric, nonhomogeneous, nonlinear object types). We define a '3-D deformable object' as an object whose three flexible degrees of freedom are characterized by viscoelastic interactions between molecules. Such an object, when an external force is applied, changes the volumetric space it occupies as well as its shape. This thus excludes such objects as cloth sheets, steel beams, and glass plates.

In order to manipulate a 3-D deformable object in the presence of gravity, we perform two main tasks. Our first task is to calculate deformation characteristics for a non-rigid object represented by a physically-based model. This model is derived from discretizing the object into a network of interconnected particles, springs, and damping elements. By assuming quasi-static system characteristics, we can utilize nonlinear partial differential equations to model the particle motion of the deformable object and calculate the deformation characteristics. For our second task, we must calculate the minimum force required to lift the deformable object. This minimum lifting force can be learned using a technique called iterative lifting. With this method, the robotic system learns the required lifting force by lifting the object with iterative measurements of force. Once the deformation characteristics and the associated lifting force term are determined, they are used as input into an index table for extracting the minimum force required for future manipulation tasks.

Based on our methodology, we show that the attributes which the system needs to know for calculating the object lifting force can be learned off-line for a wide range of three dimensional deformable objects. The attributes learned can then be mapped such that, during run-time, enough relevant attributes can be retrieved to grasp any three dimensional deformable object presented to the system. The research described in this paper addresses this issue.

RELATED PAST WORK

Manipulation of 3-D deformable objects is one of the least addressed research areas in robotics. Many robotic systems that address manipulation of deformable objects focus on force and position control of environments possessing compliant properties. In many of the research works belonging to this category, deformation of the object is usually incorporated directly into force calculation and force feedback is utilized to ensure grasp stability [1]. Some of the systems focus on deformation control versus force control. In these systems, the robot manipulator is designed to control the deformation of an object [2]. Deformable objects also appear in the field of robotics in terms of grasping with soft fingers [3]. In this category, the topics range from the utilization of software control strategies for ensuring robot compliancy to the development of specialized robotic sensing devices. Overall, these robotic systems use a restricted view in dealing with manipulation of deformable objects. On one hand, those which do not assume knowledge of deformable object attributes fail to address 3-D deformable object manipulation, with many researchers feeling that by addressing the simpler one-dimensional case, a generalized three dimensional solution can be easily found. Unfortunately, no one has, as of yet, developed a generalized solution to manipulation of 3-D deformable objects. In the following sections, we shall address these limitations and describe a technique that does not require prior in depth knowledge of object attributes for manipulation of 3-D deformable objects.

METHODOLOGY

Our main focus is to learn an adequate grasp for a deformable object. We choose to represent grasping as the act of pushing against an object from two opposite ends [6]. Our system, therefore, utilizes two cooperative manipulators, each possessing an end-effector constructed as a flat surface palm and possessing a force sensor able to detect and record any force applied to the palm's surface area.

For determination of an adequate grasp we must learn the minimum forces a multiple robotic mechanism must exert in order to lift a common deformable object cooperatively. If F_w is the force required to lift a rigid object of weight W with frictional coefficient m, we define the minimum deformable object lifting force L_f as $F_w + F_d$ where F_d is the minimum additional force term required to compensate for the deformation of the object.

We shall begin the process of determining L_f by focusing on the physical changes of the deformable body. We show that once a representation for both the external and internal positional movements of the deformable object can be retrieved, the object lifting force can be determined. In effect, we show that a relationship between object deformation and force can be learned such that an adequate grasp with minimal force can be achieved.

Deformable Object Model

At the submicroscopic scale, all solid material is composed of atoms. The grouping of atoms leads to the formation of solids. A solid can be classified as crystalline, amorphous, or a combination of both. A crystalline material is made up of crystals, an orderly array of atoms arranged in three-dimensional rows such that each atom is at an equilibrium distance from each other. This structural arrangement is called a space lattice [7] (Figure 1).

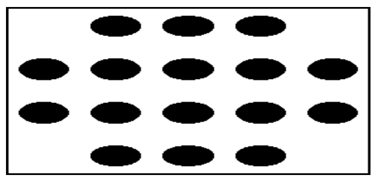

Figure 1. Space Lattice Arrangement

We shall utilize the space lattice characteristic to represent an object as a particle based system constructed from a discretized sampling of its volume. Let $\alpha>0$ represent the object discretization constant. The particle based representation of the object is thus given by a set Ψ of particles where each particle $\psi \in \Psi$[1], has an associated Cartesian position vector

$$\overline{p}_n = (x_n, y_n, z_n) = x_n\hat{i} + y_n\hat{j} + z_n\hat{k}$$

Deformation of a material is caused at the microscopic level by visco-elastic interactions between molecules. This visco-elastic interaction can be modeled by the Kelvin Model which is characterized by a spring and damper in parallel. We shall utilize this model and characterize a deformable object as a set of particles locally interconnected by damped springs (Figure 2).

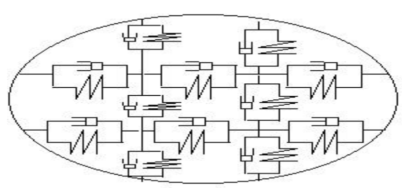

Figure 2. Network of Interconnected Particles and Springs

Calculating Deformation Characteristics

[1] where $n \leq a^3$

Let us now extract a piece of the interconnected particle system as shown in Figure 2. Let $\bar{f}_n$ represent the external force

$$(f_x, f_y, f_z) = f_x\hat{i} + f_y\hat{j} + f_z\hat{k}$$

applied to particle ψ_n. Let m_n represent the mass of particle ψ_n. Let S_n represent the number of damped springs connected to particle ψ_n. Based on the mathematical equations defining the Kelvin Model, the forces acting on the n^{th} particle are accumulation of external force, inertial force, damping force and spring force. Using Newton's law of motion, the partial differential equation for motion for the n^{th} particle can be written as:

$$\sum_{i=1}^{S_n} m_n \frac{\partial^2 \Delta\bar{p}_{n,i}}{\partial t^2}(\bar{f}_n, t) + \sum_{i=1}^{S_n} \lambda_{n,i} \frac{\partial \Delta\bar{p}_{n,i}}{\partial t}(\bar{f}_n, t) + \sum_{i=1}^{S_n} D_{n,i}\Delta\bar{p}_{n,i}(\bar{f}_n, t) = \bar{f}_n \qquad (1)$$

where D_n, the deformability coefficient, is a function of the force and the change in spring length, λ_n, the damping coefficient, is a function of the force and the instantaneous change in spring length, $\Delta\bar{p}_{n,i}(\bar{f}_n, t)$ represents the change in spring length in each Cartesian direction, and $\frac{\partial \Delta\bar{p}_{n,i}}{\partial t}(\bar{f}_n, t)$ represents the instantaneous change in spring length. We shall designate the summation $\sum_{i=1}^{S_n} \Delta\bar{p}_{n,i}(\bar{f}_n, t)$ as the particle displacement vector $\bar{d}(\bar{f}_n, t)$ and the summation $\sum_{i=1}^{S_n} \frac{\partial \Delta\bar{p}_{n,i}}{\partial t}(\bar{f}_n, t)$ as the particle displacement velocity vector $\bar{d}'(\bar{f}_n, t)$.

From Equation 1, we see that the only parameters which are not directly defined as a function of time are the mass, deformability, and damping coefficients. If we assume that the mass of the object is given, then we can classify the overall deformation of the object in terms of the deformability coefficient D and the damping coefficient λ. The algorithm we implement for determining the deformability coefficient is as follows:

1. Using both manipulators, apply a force against the object's surface. At time t_m, record the force $\bar{f}(t_m)$ felt by the manipulator.
2. Calculate the particle displacement vector $\bar{d}(\bar{f}(t_m), t_m)$
3. The deformability coefficient $D = \dfrac{\bar{f}(t_m)}{\bar{d}(\bar{f}(t_m), t_m)}$

The technique we use for determining the damping coefficient is as follows:

1. Using both manipulators, apply a force against the object surface. At time t_m , record the force $\bar{f}(t_m)$ felt by the manipulator.
2. Calculate the particle displacement velocity vector $\bar{d}'(\bar{f}_a(t_m), t_m)$ where $\bar{f}_a(t_m) = \bar{f}(t_m) - D\bar{d}(\bar{f}(t_m), t_m)$ is the damping force.

3. The damping coefficient $l = \dfrac{\bar{f}_a(t_m)}{\bar{d}'(\bar{f}_a(t_m), t_m)}$

Learning An Adequate Grasp

"Learning denotes changes in the system that are adaptive in the sense that they enable the system to do the same task or tasks drawn from the same population more efficiently and more effectively the next time" [8]. In this research, we wish to learn how to efficiently and effectively grasp a deformable object. To learn the characteristics of an adequate grasp, we must determine the relationship between mass, deformation, and force. Once this relationship is learned, we can utilize these factors to maintain a firm grasp on any deformable body by comparing the current run-time mass/deformation of the object with the learned relationship. When they are equivalent, we can retrieve the minimum force required for grasping a deformable object.

We assume that an object first presented to the system is initially in an equilibrium state. Thus the summation of all forces inherent to the object converges to zero. To begin the iterative lifting process we apply a force F_w to the object and lift the object until the object particles have stabilized their positions. If, at this time, the object has not slipped, the object is in equilibrium and a firm grasp on the object has been achieved. This then is the object lifting force L_f. We record its value at this time and terminate the lifting process. If the object has slipped from the manipulator grasp, we increase the applied manipulator force and repeat the lifting process. Eventually a minimum force will be reached which, when applied, will be able to lift the deformable object.

After learning values for the lifting force, we store this information into an index table where given the mass, deformability, and damping coefficients we can extract the minimum lifting force required for subsequent deformable object manipulation tasks.

EXPERIMENTAL SETUP

We have validated our methodology for the manipulation of 3-D deformable objects using two experimental setups. The first setup consists of the implementation of the algorithm in a simulated environment. The second involves a physical implementation of the algorithm whose outcome is compared with the simulation results in order to test the real world validity of the developed methodology. We utilize four deformable objects, each with different deformation characteristics and weights to test the learning algorithm. Based on the results (Table I), we show that we can achieve an error level of 14% with respect to the physical and simulation lifting force.

	Calculated			**Simulation**
	Deformability (N/cm)	*Damping (Ns/cm)*	*Lifting Force (N)*	*Lifting Force (N)*
Sponge	49.18	6.47	0.84	0.7
Cotton	13.03	0.33	1.72	2.23
Sand	30.02	0.47	5.97	4.86
Water	10.52	0.00	10.23	11.13

Table I. Implementation Results

CONCLUSIONS

In this paper, we discussed a learning methodology capable of extracting the minimum forces necessary to manipulate 3-D deformable objects without assuming prior in-depth knowledge of object attributes. Our methodology was able to incorporate a wide variety of deformable object types. We validated our developed algorithm with two sets of experiments. The first experimental results were derived from the implementation of the algorithm in a simulated environment. The second set involved a physical implementation of the technique whose outcome was compared with the simulation results to test the real world validity of the developed methodology. Based on the results, we are able to show that even using a number of simplifying assumptions for a simulation model, we can achieve both a physical and simulation lifting force for the same deformable object that only differ from each other by a maximum of 14%. In fact, with more accurate equipment, we could use the results extracted from the simulation to get an approximate measurement of the lifting force without having to physically perform the iterative lifting process. This force could be directly input into the robotic device for lifting. The iterative lifting process would then only need to be performed to incrementally compensate for the approximation error with a given deformable material.

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